Efficient Image Enhancement Using Illumination Map Technique

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Abstract- *Digital scenes are used in many applications like object detection and tracking medical applications and satellite images and many other PC based applications. Pictures captured during day time having a good visibility with high dynamic range and useful for extracting the details. But the pictures captured during night time or in low light condition having a low dynamic range with noise and indistinguishable details. A simple yet effective ALM method is proposed. More concretely, the explanation of each pixel is first probable individually by sentence the greatest value in R, G and B channels. Further, we refine the initial illumination map by imposing a structure prior on it, as the final illumination map. Having the well construct clarification map, the improvement can be achieved consequently. Experiments on a number of challenging low-light images are present to reveal the efficacy of our enhancement and show its superiority over several state-of-the-arts in terms of image quality and efficiency.*

Keywords- Illumination Estimation, Illumination Transmission, Augmented Lagrangian Multiplier (ALM)

I. INTRODUCTION

The actual problem is identified the next step in Problem Analysis is to crumble the problem into smaller separate basics and to further refine their individual characteristics. The intent is to gain additional insights into the problem, and subsequently, a better understanding of the customer needs. Decomposition and refinement are activities of Problem Decomposition. Problem decay involves a series of steps by means of which a set of needs is obtained, from which the supplies are derived. Like its predecessor, Problem Decomposition is an iterative process that begins with root cause analysis. This supposes of course, that the actual problem has been identified and has a well-defined problem statement. In addition, we recommend that the analyst be educated about the problem specific aspects of the customer's domain and the environment within which the new/modified system will eventually function. This indoctrination either outlines or provides the basis for (a) defining the solution boundaries and (b) identifying the constraints to be imposed on the solution space, e.g., economic, political, technical, etcetera.

As mentioned above, Problem disintegration is an iterative process that often involves frequent meetings with the customer. Prior to each meeting the analyst needs to ensure that he/she has identified the appropriate set of stakeholders (or meeting participants), set a meeting agenda, and has outlined each participant's role and responsibilities prior to the meetings. To support problem modification, each meeting must have an alert objective and employ planned activities that support the achievement of that objective, e.g., recording corrosion machinery and evolved needs, and monitoring/controlling the meeting process. Finally, at the end of each meeting, the identified "set of needs" are evaluated relative to their correctness, completeness and non-ambiguity. The last set of purchaser needs can be "validate" (in a loose sense) next to the Con-Ops document or beside the set of high-level supplies shaped during the systems engineering process. As exemplify in Figure 1, the set of customer needs are then provide as input to the supplies elicitation process and form the basis from which the supplies (or solution specification) are derived.

As noticed in, upturned streak images look like haze images, as shown. Based on this inspection, the authors of instead resorted to debase the upturned low-light images. After Dehazing, the obtained unrealistic images are inverted again as the final enhanced results. Recently, Li et al. follow this trade line and additional improved the visual quality by first over segmenting the effort image and then adaptively Denoising different section. Even though the above Dehazing-like methods can provide reasonable results, the basic model they rely on is lacking in physical explanation. By contrast, our method has clear physical intuition. Our method belongs to the Retinex-based category, which intend to improve a low-light image by estimating its clarification map. It is worth noting that, different from the traditional Retinex-based methods like that decompose an image into the reflectance and the illumination components, our method only estimates one factor, say the illumination, which shrinks the answer space and reduce the computational cost to reach the preferred result. The illumination map is first constructed by finding the maximum intensity of each pixel in R, G and B channels. Then, we exploit the structure of the illumination to refine the illumination map.

II. HISTORICAL OVERVIEW

A contrast enhancement algorithm based on the layered difference representation is proposed in this work. We first represent gray level differences at multiple layers in a tree-like structure. Then, based on the observation that gray-level differences, occurring more frequently in the input image, should be more emphasized in the output image, we solve a constrained optimization problem to derive the transformation function at each layer. Finally, we aggregate the transformation functions at all layers into the overall transformation function. Simulation results demonstrate that the proposed algorithm enhances images efficiently in terms of both objective quality and subjective quality. Contrast enhancement techniques can alleviate these problems by increasing contrast ratios and bringing out hidden details. Therefore, difference improvement is an necessary step in various image processing applications, such as digital photography and visual surveillance.

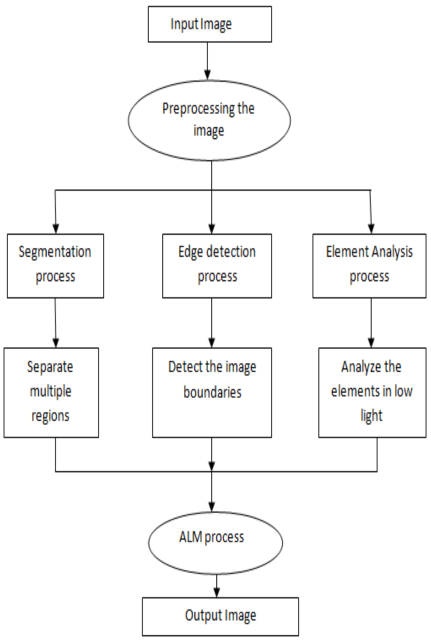
An imperative position in image processing and analysis among various enhancement algorithms, Retinex-based algorithms can efficiently enhance details and have been widely adopted. Since Retinex-based algorithms regard illumination removal as a default preference and fail to limit the range of reflectance, the naturalness of non-uniform illumination images cannot be effectively preserved. However, honesty is needed for image development to achieve enjoyable perceptual quality. In order to preserve sincerity while attractive details, we propose an improvement algorithm for non-uniform explanation images. In general, this paper makes the following three major contributions. First, a lightness-order error measure is proposed to access naturalness preservation objectively. Second, a bright-pass filter is proposed to decompose an image into reflectance and clarification, which, respectively, conclude the details and the sincerity of the image.

A weighted variation model to estimate both the reflectance and the illumination from an observed image shows that, it is generally adopt for ease of modeling, the log-transformed image for this task is not ideal. Based on the previous investigation of the logarithmic transformation, a new weighted variation model is proposed for better prior representation, which is imposed in the regularization terms. Different from conventional variation models, the proposed model can preserve the estimated reflectance with more details. Moreover, the proposed model can suppress noise to some extent. An alternating minimization scheme is adopted to solve the proposed model. Experimental results demonstrate the effectiveness of the proposed model with its algorithm.

The joint low-light image improvement structure for theEnhancement and demising is proposed. First, the low-light image is segmented into super pixels, and the ratio between the local standard deviation and the local gradients is utilized to estimate the noise texture level of each super pixel. Then the image is inverted to be processed in the following steps. Based on the noise texture level, a smooth base layer is adaptively extracted by the BM3D filter, and another detail layer is extracted by the first order differential of the inverted image and smoothed with the structural filter. These two layers are adaptively combined to get a noise-free and detail-preserved image. At last, an adaptive enhancement parameter is adopted into the dark channel prior debasing process to enlarge contrast and prevent over/under enhancement. Experimental results demonstrate that our proposed method outperforms traditional methods in both subjective and objective assessments.

A. BACKGROUND DETAILS

Our process belongs to the Retinex-based category, which intends to enhance a low-light image by estimation its clarification map. It is worth noting that, different from the traditional Retinex-based methods like that decompose an image into the reflectance and the illumination components, our method only estimates one factor, say the clarification, which shrink the answer space and reduces the computational cost to reach the preferred result. The illumination map is first constructed by finding the maximum intensity of each pixel in R, G and B channels. Then, we exploit the structure of the illumination to refine the illumination map. An Augmented Lagrangian Multiplier (ALM) based algorithm is given to exactly solve the refinement problem, while another sped-up solver is designed to intensively reduce the computational load. Experiments on a number of testing images are conducted to expose the advantages of our method in contrast with other state-of-the-art methods.



B. *Preprocessing*

Images suffering from low quality of enhancement are considered to be input image such as image captured in low light which suffers the visibility of background objects. Preprocessing is used to remove the noise from the given input image by using Gaussian median filter. Pre processing is done on the captured image to prepare it for further analysis. Such processing includes: Threshold to reduce a grayscale or color image to a binary image, reduction of noise to reduce extraneous data, segmentation to separate various components in the image, and, finally, contraction or margin exposure to allow easier following detection of related features and objects.

C. *Segmentation and Edge Detection*

To partition the image into its constituent parts we are using and Non maximum Suppression technique. In this process it considers 9 pixels neighboring around each edge that is already over a threshold and interpolates edge strengths E at neighborhood boundaries at negative and positive gradient directions from centre pixel. If the pixel under consideration is not greater than these two values then it is suppressed.

An edge is a set of connected pixels that lie on the boundary between two regions and the edge information in an image is found by looking at the relationship of pixel with its neighborhoods. If a pixel's gray-level value is similar to those around it, there is probably not an edge at that point. If a pixel's has neighbors with widely varying gray levels, it may present an edge point. The edge representation of an image significantly reduces the quantity of data to be processed, yet it retains essential information regarding the shapes of objects in the scene.

D. *Image Refocusing*

An image processing method for synthesizing refocused images from a single input photograph containing some defocus blur. First, we restore a sharp image by estimating and removing spatially-variant defocus blur in an input photograph and then, the image is refocused into the gray scale pixel regions of image (a) by clearly zooming into the region of the edge detected image for a clear focus as given in image(b)

E. *Image Analysis*

Image analysis is a computer-based process of extracting quantitative information from images. The process begins with the input of an image and ends with the output of numerical data. In the numerical data of the image is represented in measures of standard deviation and mean value of the image.

F. *Element Analysis*

Finite element analysis is the most used methodology to predict the mechanical behavior of a large spectrum of materials which are hidden in the low light and suffers from visibility as it is in image (a) and the elements in the dark regions are gets analyzed by adjusting the threshold value to get visibility as in image (b).

III. MATH

G. *Image Gradient*

The first derivative pixel in the horizontal direction (x) and the vertical direction (y) will show the image gradient therefore the gradient of an image is given as

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

The gradient points in the direction of most rapid change in intensity and the direction is given by

$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

The edge strength is given by the gradient magnitude

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

At first, Gaussian filter is applied to smooth the image and remove noise and then the non maximum suppression technique is applied to get spurious response to segment as shown in the edges by applying the intensity gradient value of the image, the threshold values are given to determine potential edges and track the edge to finalize the edges of the image by suppressing all the other weak edges.

H. *Illumination Map Estimation using Augmented Lagrangian Multiplier:*

An Augmented Lagrangian Multiplier (ALM) based algorithm is given to exactly solve the image enhancement problem Augmented Lagrangian methods are a certain class of algorithms for solving constrained optimization problems. The Augmented Lagrangian is not the same as the method of Lagrange multipliers.

To estimate the illumination by seeking the maximum value of three colour channels, say Red, Green and Blue. But this Intrinsic image decomposition involves three factors such as Lambertian Shading(T), Reflectance (R), and Specularities (C) which is expressed as,

$$L = R \circ T + C \qquad (1)$$

to handle non-uniform illuminations, we alternatively adopt the following initial estimation

$$\hat{T}(x) \xleftarrow[c \in \{R,G,B\}]{} max\ L^c(x) \qquad (2)$$

For each individual pixel x. The principle used in the above operation is that the illumination is at least the maximal value of three channels at a certain location. The obtained ^T(x) guarantees that the recovery will not be saturated, because of

$$\boldsymbol{R}(x)/(max_c L^c(x) + \in) \qquad (3)$$

where ϵ is a very small constant to avoid the zero denominator. We point out that the goal of this work is to non-uniformly enhance the illumination of low-light images, instead of eliminating the colour shift caused by light sources.

As mentioned, another widely used model is based on the observation that inverted low-light images 1 − L look similar to haze images.

$$1 - \boldsymbol{L} = (1 - \boldsymbol{R}) \circ \hat{T} + a(1 - \hat{T}), \qquad (4)$$

where a represents the global atmospheric light. Although the visual effect of inverted low-light images 1−L is intuitively similar to haze images, compared to the model (1) the physical meaning of the above remains vague. Below we intend to show the relation between (4) and (1). Let us here recall the dark channel prior, a commonly used prior to estimate the transmission map for 1− L as follows:

$$\hat{T}(x) \leftarrow 1 - min_c \frac{1 - L^c(x)}{a} = 1 - \frac{1}{a} + max_c \frac{L^c(x)}{a} \qquad (5)$$

Substituting (5) in (4) yields

$$\boldsymbol{R}(x) = \frac{L(x) - 1 + a}{(1 - \frac{1}{a} + max_c \frac{L^c(x)}{a} + \in)} \qquad (6)$$

We can see that when a = 1, both (3) and (6) reach the same result. But when it gets away from 1, the equivalence between the models (6) and (3) breaks,

So the atmospheric light is greater than 0:95, the visual difference between using (6) and using (3) is still conspicuous. In this work, we rely on the model (3) without involving the atmospheric light a

In this work, we employ (2) to initially estimate illumination map ^T, due to its simplicity, although various approaches in past decades. Most of these improvements essentially consider the local consistency of illumination by taking into account neighbouring pixels within a small region around the target pixels.

The representative ways are:

$$\hat{T}(x) \xleftarrow[\max y \in \Omega(x), c \in \{R,G,B\}]{} L^c(y)$$
$$\hat{T}(x) \xleftarrow[mean\ y \in \Omega(x), \max c \in \{R,G,B\}]{} L^c(y) \qquad (7)$$

Here (x) is a centre region of pixel x and y is the location index ,within the region. These schemes can somewhat enhance the local consistency, but they are structure-blind. In the following, we provide a more powerful scheme to achieve this goal. A “good” solution should simultaneously preserve the overall structure and smooth the textural details. To address this issue, based on the initial illumination map ^T, we propose to solve the following optimization problem

$$\min(T)\left\|\hat{T}-T\right\|_F^2+a\|W\circ\nabla T\|_1 \quad (8)$$

Were, α is the coefficient to balance the involved two terms and, ‖ .‖F and ‖ . ‖1 designate the Frobenious and l1 norms,

Further, W is the weight matrix, and ∇T is the first order derivative filter. In this work, it only contains ∇_hT (horizontal) and ∇vT (vertical). In the objective (8), the first term takes care of the fidelity between the initial map $\hat{T}$ and the refined one T, while the second term considers the (structure-aware) smoothness. Prior to discussing possible strategies of constructing W, we give two solvers in the next two sub-sections to resolve problem (8) such as the mean and standard deviation values are given for solving ,to enhance the image.

IV. CONCLUSION

A successful and efficient method to improve the quality and enhancement of low-light images using the illumination map estimation technique is done to develop and the illumination consistency. We have planned to find the exact best solution to the target pixels by identifying the grayscale pixel, and calculating the mean value and standard deviation of the image and applying in the illumination algorithm which solves the enhancement problem by also saving of time. Moreover, our model is general to different (structure) weighting strategies. The experimental results have revealed the maximum of each of the three RBG channels by applying along to the contrast of the image so that the reality of the image is being preserved throughout the illumination estimation process. This method can feed up on applications, such as edge detection, object recognition and tracking objects and thus improve their performance and quality of vision.

REFERENCES

[1] C. Lee and C. Kim, “Contrast enhancement based on layered difference representation,” TIP, vol. 22, no. 12, pp. 5372–5384, 2013.

[2] S. Wang, J. Zheng, H. Hu, and B. Li, “Naturalness preserved enhancement algorithm for non-uniform illumination images,” TIP, vol. 22, no. 9, pp. 3538–3578, 2013.

[3] X. Fu, D. Zeng, Y. Huang, X. Zhang, and X. Ding, “A weighted variational model for simultaneous reflectance and illumination estimation,” in CVPR, pp. 2782–2790, 2016.

[4] L. Li, R. Wang, W. Wang, and W. Gao, “A low-light image enhancement method for both denoising and contrast enlarging,” in ICIP, pp. 3730–3734, 2015.

[5] R. Grosse, M. Johnson, E. Adelson, and W. Freeman, “Ground-truth dataset and baseline evaluations for intrinsic image algorithms,” in ICCV, pp. 2335–2342, 2009.

[6] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Image denoising by sparse 3d transform-domain collaborative filtering,” TIP, vol. 16, no. 8, pp. 2080–2095, 2007.

[7] S. Gu, L. Zhang, W. Zuo, and X. Feng, “Weighted nuclear Norm minimization with applications to image denoising,” in CVPR, pp. 2862–2869, 2014.

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